

1 **Remote Sensing Techniques for Predicting Evapotranspiration from Mixed Vegetated**
2 **Surfaces**

3 Hamideh Nouri¹, Simon Beecham², Fatemeh Kazemi^{1,3}, Ali Morad Hassanli^{2,4}, Sharolyn Anderson^{2,5}

4 ¹SA Water Centre for Water Management and Reuse, University of South Australia, Adelaide, Australia

5 ²School of Natural and Built Environments, University of South Australia, Adelaide, Australia

6 ³Ferdowsi University, Mashhad, Islamic Republic of Iran

7 ⁴School of Agriculture, Shiraz University, Shiraz, Islamic Republic of Iran

8 ⁵Barbara Hardy Institute, University of South Australia, Adelaide, Australia

9

10 Corresponding author: Hamideh Nouri (Hamideh.Nouri@unisa.edu.au & Hamideh.Nouri@mymail.unisa.edu.au)

11

12

13 **Abstract**

14 Evapotranspiration (ET) as the key component of hydrological balance is the most difficult
15 factor to quantify. In the last decades, ET estimation has been benefitted from advances in
16 remote sensing particularly in agricultural fields. However, quantifying evapotranspiration
17 from mixed landscape vegetation environs is still complicated and challenging due to the
18 heterogeneity of plant species, canopy covers, microclimate, and because of costly
19 methodological requirements. Extensive numbers of studies have been conducted in
20 agriculture and forestry that alternatively ought to be borrowed for mixed landscape
21 vegetation studies with some modifications. This review describes general remote sensing-
22 based approaches to estimate ET and their pros and cons. Considering the fact that most of
23 them need extensive time investment, medium to high level of skills and are quite expensive,
24 the simplest approach; interface, is recommended to apply for mixed vegetation. Then, VI-
25 based approach was discussed for two categories of agricultural and non-agricultural
26 environs. Some promising studies were mentioned to support the suitability of the method for
27 mixed landscape environs.

28

29 **Key words: remote sensing; evapotranspiration; satellite/airborne images; spatial and**
30 **temporal heterogeneity; NDVI**

31

32

33 **1. Introduction**

34 Quantification of evapotranspiration as a fundamental requirement in the local and global
35 assessment and management of climate change, land use, water budget and irrigation is of
36 both interest and concern. Water loss by evaporation can occur from three main sources of
37 soil, vegetation surface or atmosphere (Burt et al., 2005). Soil evaporation is affected by soil
38 moisture status, soil physical and chemical characteristics, tillth conditions, soil cover (e.g.
39 mulch), and ecological parameters. Evaporation of vegetation surface is influenced by
40 vegetation type, species, canopy cover, microclimate, and water availability to the plants by
41 precipitation or irrigation. Atmosphere evaporation may happen from irrigation water (e.g.
42 sprinkler droplets) that varies for different irrigation systems and meteorological conditions.
43 There is a specific form of evaporation from plants tissues that is named transpiration. The
44 sum of evaporation and transpiration is collectively termed evapotranspiration (ET) which is
45 the main consumptive of irrigation and precipitation in vegetation environs (Nouri et al.,
46 2012). ET occurs not only from vegetation leaves but also from stems, flowers and roots.
47 Evapotranspiration, as an important component of the hydrological cycle affects soil water
48 availability, soil water chemistry, and vegetation healthiness and aesthetics (Johnson and
49 Belitz, 2012;Lucke et al., 2011;Jovanovic and Israel, 2012). Considering the fact that more
50 than 90% of annual rainfall is consumed by ET in arid and semi-arid areas (Glenn et al.,
51 2007), the importance of ET measurement is not deniable.

52 For decades, weather-based methods (Allen, 2000;Allen et al., 1998), soil moisture
53 measurements (Allen et al., 1998;Nouri et al., 2012), and surface energy balance approaches
54 have been the dominant techniques for predicting vegetation ET (Allen et al., 2011a;Li et al.,
55 2009;Silberstein et al., 2001;Tanaka et al., 2008;Yunusa et al., 2004). Broad numbers of
56 numerical models were introduced for the local and regional ET measurements but they
57 mostly need detailed input data of soil, vegetation and climate. It limits their application to

58 the specific areas with the long-term comprehensive records of required input data (Kustas
59 and Norman, 1996).

60 Over last decade, ET estimation has been improved through advanced technologies and
61 increasingly well-developed infrastructure and instruments particularly remote sensing. ET
62 estimation using satellites imagery is the most efficient and economic technology that can
63 employ for a broad range of pixel to global scales. It also was coupled to some empirical
64 methods to simplify the ET measurement and shorten the input data requirements. Later on,
65 in order to minimise atmospheric effects on optical data (e.g. clouds in the images),
66 microwave imagery took the place in measuring surface moisture and surface temperature
67 (Kustas and Norman, 1996).

68 Climate change and water availability are major concerns today, indicating the importance of
69 water and carbon flux assessments. Satellite imagery provides the required information to
70 assess surface water, carbon and energy exchanges through quantifying certain biochemical
71 and biophysical parameters mainly associated with photosynthesis and chlorophyll content.
72 Although both ET and carbon exchanges are controlled by stomata, they have been remotely-
73 sensed and modelled in different ways using different biophysical parameters (Anderson et
74 al., 2008).

75 Yet despite a broad range of promising technologies and sophisticated facilities, ET
76 estimation of urban parklands remains insufficiently characterized. This complexity of this
77 challenge is due to diversity in water needs of heterogeneous and multi-story mixed
78 vegetation systems (Drexler et al., 2004; Sumantra, 2011). The value of urban green spaces
79 and particularly urban parklands has been studied comprehensively (Weber and Anderson,
80 2010). The important role of parklands in the areas of public health and well-being indicates
81 the critical importance for a better understanding of parkland water demand. Consequently

82 this study is focused on ET from urban parklands as the main component of vegetation water
83 requirement.

84 ET estimation using hydrological methods (e.g. water balance), micro-meteorological
85 methods (e.g. energy balance) or direct ET measurement methods can only be considered as
86 point measurements. Extrapolation of ET rates from a point to a large area decreases the
87 accuracy of the estimation. Analysis of satellite or airborne images using remote sensing
88 techniques is a practical method for developing the spatial variation of ET at a regional scale
89 (Vinukollu et al., 2011).

90 Due to the highly distributed nature of mixed landscape vegetation, remote sensing could be
91 an ideal technique of ET measurement for these types of landscapes. ET measurement by
92 remote sensing provides an area-based estimation that can be updated frequently. Also,
93 because it has the capability of quantifying the vegetation characteristics including species
94 composition, vegetation type and moisture status for a broad area, more accurate results
95 would be obtained.

96 Variety of complicated RS-based models and algorithms has been introduced and evaluated
97 for different vegetation types in different scales. They are mostly comparable in the pixel-
98 scale spectral homogeneity assumption. In the mixed landscape planting, diversity of
99 vegetation is in contrast with the spectral homogeneity assumption. Additionally,
100 inconsistency in reflectance properties of mixed vegetation may lead in misclassification of
101 land covers. However, image processing advances besides high spatial, spectral and temporal
102 resolution satellite/airborne images diminish the mentioned challenges in classification and
103 permit improved records of land cover changes (Small, 2003; Small and Lu, 2006).

104 With a fast growing interest in the implementation of green infrastructure which often
105 involved mixed vegetation types, the current study has mainly focused on the application of

106 remote sensing techniques in heterogeneous parklands. In ET estimation of small urban green
107 spaces, biophysical components of urban ecosystem should be considered. It was
108 comprehensively discussed by Ridd (1995). He introduced a Vegetation-Impervious-Soil
109 surfaces (VIS) model to consider the major urban features affecting evapotranspiration rate in
110 ET measurement. Further studies used the VIS model and match it with the image processing
111 methodology (Phinn et al., 2002) to get a better result. In 2012, Wang and Dickson
112 recommended combination of field and satellites-based measurements to obtain a more
113 precise estimation of daily, monthly and annually ET rates (Wang and Dickinson, 2012). It
114 should be noted that for each particular approach; field-based, RS-based or combined
115 approaches, there are specific assumptions that may impose some limitations or restrictions to
116 the capability and applicability of the method besides some uncertainty or errors to the
117 outcomes.

118 Others have written full reviews of ET and remote sensing (Courault et al., 2005a; Glenn et
119 al., 2007; Kalma et al., 2008; Li et al., 2009), thus this paper concentrates on relevant RS
120 approaches for predicting ET from mixed vegetated surfaces mainly at a local scale. It also
121 summarizes the merits and drawbacks of each method.

122 Remote sensing methods for estimating ET

123 Different categories were introduced for ET estimation using remote sensing (Allen et al.,
124 2011a; Kustas and Norman, 1996; Li et al., 2009). The most comprehensive categorisation was
125 proposed by Courault et al. (2005a) and well discussed by Calcagno et al. (2007). They
126 classified remote sensing methods for ET estimation into four groups, namely empirical
127 direct, residual, inference, and deterministic methods.

128 2.1 Empirical direct methods

129 Assessing the energy balance using some **land** surface properties like albedo, canopy cover,
130 leaf area index (LAI) and surface temperature is the principle of ET estimation by remote
131 sensing.

$$132 R_n = LE + H + G \quad (1)$$

133 The net radiant energy (R_n) is divided to soil heat flux (G) and atmospheric fluxes (sensible
134 heat flux H and latent energy exchanges LE).

135 Observed **heterogeneous vegetated surface**s can be considered as a single layer (component)
136 or multiple layers (two components of soil and vegetation). In a single layer approach, net
137 radiation is related to the whole surface and sensible heat flux is related to the aerodynamic
138 resistance between surface and above surface (2m height). Dynamic resistance is affected by
139 wind speed, atmospheric stability, roughness lengths for momentum and heat. However,
140 momentum and heat variables (e.g. surface temperature) significantly vary for different
141 vegetation height and density. In multilayer approaches, sensible heat flux considers both soil
142 and vegetation resistance with the equivalent temperature (Courault et al., 2005a).

143 **Due to the importance of biophysical and biochemical cycles associated with photosynthesis**
144 **processes, some coupled modelling systems have benefited from the spatial and temporal**
145 **correlation of ET and CO₂ to improve the accuracy of ET estimation derived from remote**
146 **sensing surface energy and water balance models (Anderson et al., 2008; Kim and Leith,**
147 **2003). For instance, Anderson et al. (2008) used thermal satellite imagery to implement an**
148 **analytical light-use efficiency based model (computing carbon assimilation and transpiration**
149 **at the canopy scale) of bulk canopy resistance within a two source energy balance approach.**
150 **Their results confirmed an improvement in energy budget assessment compared to in-situ**
151 **eddy covariance tower observations mainly by reduction in prediction errors for the latent**
152 **heat flux. In another study, Houborg et al. (2011) investigated integrating the analytical light-**

153 use efficiency based model using airborne images into a two source energy balance model for
154 predicting land surface CO₂ and energy fluxes for a corn field. They found that the calibrated
155 analytical light-use efficiency based model could be correlated with airborne leaf chlorophyll
156 content and hourly water, carbon and energy fluxes derived from a two source energy balance
157 model.

158 For an urban area, the most sensitive parameters in the surface energy balance are the total
159 latent heat flux of the natural surface and the total sensible heat flux of the urban surface.
160 Local changes in the total sensible heat flux of the urban surface may result in approximately
161 a 20% change in the total heat flux. These parameters are very important when dealing with
162 mesoscale studies. Due to the relatively small spatial scale of parklands, the available
163 literature does not currently support the need for including biochemistry surface parameters
164 in the estimation of ET in parklands. This could be potentially of more concern in urban
165 boundary layer meteorology modelling since the urban surface often involves buildings that
166 disturb air flow and generate turbulent eddies with different physical parameters of albedo
167 and evaporation (Flagg and Taylor, 2011).

168 Empirical direct methods are characterised by a semi-empirical relationship between net
169 radiation and cumulative surface and air temperature differences. Air temperature is
170 measured by a ground-based weather station while surface temperature is obtained from
171 satellite imagery. These methods are usually based on the theoretical assumption of a
172 constant value of the ratio H/R_n during the day and no soil flux:

$$173 \quad ET_{24} = R_{n24} + A - B (T_s - T_a) \quad (2)$$

174 where ET_{24} is daily ET, R_{n24} is net daily radiation, $T_s - T_a$ is the difference between the mid-
175 afternoon surface temperature and the maximum air temperature (this is termed the Stress

176 Degree Day or SDD), and A and B are calibration parameters. This method can be accurate in
177 a local scale study area if calibrations and interpolations are accurate.

178 Due to the strong relationship between Vegetation Indices (VI) and surface temperature,
179 Carlson et al. (1995) developed a trapezoidal scheme to determine a relationship between
180 SDD and NDVI (Normalized Difference Vegetation Index) that resulted in an appropriate
181 measurement of soil moisture conditions in different depths. They suggested that the strong
182 relationship between surface radiant temperature and NDVI may yield in more accurate
183 estimation of soil moisture status. Gillies et al. (1997) employed multispectral images to
184 estimate surface soil water content, vegetation cover, and surface energy fluxes in the mixed
185 landscape vegetation of trees and grasses and compared the results with ground
186 measurements. In spite of many uncertainties in mixed vegetation, soil types, shading and etc.
187 results showed comparable errors to ground measurement. Yuan and Bauer (2007)
188 determined the amount of urban mixed vegetation and land surface temperature via satellite
189 image analyses and then measured latent heat flux and evapotranspiration. Their analyses
190 indicated that the relationship between NVDI and land surface temperature varies seasonally
191 so they recommended using thermal infrared remote sensing in mixed landscape environs.

192 Anderson et al. (2012) described the uniqueness of land surface temperature maps (thermal
193 images) in ET monitoring and mapping over large areas. Improvement in the spatio-temporal
194 resolution of images has both increased accuracy and reduced errors in ET estimation.

195 *2.2 Residual methods*

196 In this method, empirical and physical relationships are combined to estimate the energy
197 balance components (except ET) directly through remote sensing (Kalma et al., 2008; Su,
198 2002a). ET is estimated as the residual of the energy balance equation. Latent energy
199 exchange is estimated using a linear relationship between latent energy exchanges and

200 surface air temperature differences at a specific time (Boegh et al., 1999;Calcagno et al.,
201 2007). Reasonable accurate results can be obtained from this approach in midday. However,
202 ground-based weather data is required to interpolate the results for the longer periods of daily
203 or monthly records.

204 Several models have been introduced and employed to investigate the spatial variation of
205 radiance and satellite image reflectance. Reliable but complex methods are based on different
206 models: Surface Energy Balance Algorithm for Land or SEBAL (Teixeira et al., 2009;Sun et
207 al., 2011;Timmermans et al., 2007); Surface Energy Balance Index or SEBI (Yang and
208 Wang, 2011;Galleguillos et al., 2011); Simplified Surface Energy Balance Index or S-SEBI
209 (Roerink et al., 2000;Sobrino et al., 2005); Surface Energy Balance System or SEBS
210 (Rwasoka et al., 2011;Jia et al., 2003); and Two-Source Energy Balance or TSEB (Yao et al.,
211 2010;Tang et al., 2011). The SEBAL method predicts the energy fluxes at a regional scale.
212 Remote sensing images are employed to estimate net radiation and soil heat flux
213 (Bastiaanssen et al., 1998;Tasumi et al., 2005). However, the SEBAL method does not use
214 precipitation as an input parameter in ET estimation so the rainfall impact cannot be mirrored
215 in the results (Anderson et al., 2008).

216 The SEBAL model has been widely used to estimate ET in different climates, ecosystems
217 and land covers, predominantly in agricultural studies. This model is a thermal infrared
218 remote sensing-based method that includes triangular approaches (Carlson et al., 1994; Jiang
219 and Islam, 2001), two-source energy balance approaches (Long and Singh, 2012a; Norman et
220 al., 1995), and one-source approaches (Su, 2002). SEBAL considers groups of pixels inside
221 the analysed area as being either dry or wet. In the dry pixels, the latent heat is assumed to be
222 zero, so the available energy is totally transformed into sensible heat flux. For the wet pixels,
223 sensible heat flux is theorized to zero and surface and air temperatures are assumed to be
224 equal to each other (Calcagno et al., 2007). The SEBI model follows the principles of SEBAL

225 by hypothesizing the reflectance of maximum temperature for dry pixels and the reflectance
226 of minimum temperature for wet pixels (Roerink et al., 2000). The main distinction between
227 SEBI and SEBAL are the differences in definition, calculation, and interpolation of
228 maximum and minimum latent heat fluxes for a given set of layers (Li et al., 2009). The S-
229 SEBI model simplifies the SEBI model by obtaining the extreme temperatures for the dry and
230 wet pixels (Roerink et al., 2000). The SEBS model involves three data sets of information.
231 The first set includes albedo, emissivity, temperature, LAI, and vegetation height. The second
232 is a meteorological data set including temperature, air pressure, humidity, and wind. The third
233 data set includes direct or modelled solar radiation measurements. In contrast to the SEBAL
234 model, the SEBS model does not assume that the sensible heat flux is zero for wet pixels (Su,
235 2002b). Senay et al. (2011) developed an enhanced version of the Simplified Surface Energy
236 Balance (SSEB) model and to evaluate its performance using the established METRIC
237 model. They claimed that SSEB can be used to estimate ET with inputs of surface
238 temperature, NDVI, DEM, and reference ET.

239 *2.3 Inference methods*

240 This method is termed inference method or vegetation indices. It is based on RS application
241 to measure a plant adjustment factor (such as crop factor or landscape factor) to determine the
242 actual evapotranspiration. Given the formula

$$243 \quad ET_{\text{plant}} = K_{\text{plant}} * ET_{\text{ref}} \quad (3)$$

244 The actual evapotranspiration rate (ET_{plant}) is readily calculated from the reference
245 evapotranspiration (ET_{ref}) and plant adjustment factor (K_{plant}). Equation 3 has been broadly
246 described in FAO-56 (Allen et al., 1998). Reference evapotranspiration is achieved by the
247 ground measurement and adjustment factor is applied to reduce evapotranspiration rate based
248 on plant water need (Nouri et al., 2012). In this method, the main factors required for

249 analyses are crop characteristics and meteorological data. Crop resistance to transpiration is
250 related to differences in plant height, roughness, reflection, density, and rooting system and
251 these all vary in the plant's different growth stages. Consequently these variables all need to
252 be measured periodically within the plant growing season. The main meteorological data
253 include solar radiation, temperature, humidity, and wind. For more precise estimation, a
254 complex alternative approach for crop/plant coefficient (dual crop coefficient) is used by
255 separately considering transpiration from the plant canopy and evaporation from the soil. In
256 this approach measuring solar radiation interception by vegetation cover (for non-stressed
257 plants) yields the basal crop coefficient. Predicting available energy at the soil surface can
258 lead to estimate of soil evaporation (Allen, 2000).

259 Application of the field-based approach in the mixed landscape vegetation introduces comes
260 along with some limitations. Heterogeneity of plant species, vegetation density and
261 microclimate yields in a high variation of plant evapotranspiration rates even in small scales.
262 However, some approaches were introduced and applied for the mixed vegetation environs.
263 They comprehensively discussed by Nouri et al. (in-review). RS-based method is an
264 alternative trustable approach that facilitates considering diversity of mixed vegetation in ET
265 estimation.

266 Inference methods use the reflectance value of the red (R) and Near Infrared (NIR) bands to
267 predict VI (particularly NDVI) or LAI (Leaf Area Index). Although it requires ground-based
268 calibration, it is still more affordable than empirical and residual methods those need high
269 cost detailed field measurements (Courault et al., 2005a). Many studies have been conducted
270 to find the correlation between crop coefficients and VI and particularly NDVI (Consoli et
271 al., 2006; Neale et al., 2005; O'Connell et al., 2009; Trout et al., 2008). However, Allen et al.
272 (2005) found that the relationship between crop coefficients and VI exists but emphasizes that

273 the specific relationship is not transferable. He stresses that this is true particularly because of
274 irrigation effects on soil moisture and water stress conditions.

275 *2.4 Deterministic methods*

276 This method is established based on the complex soil, vegetation, atmosphere transfer models
277 (SVAT). Remote sensing can be employed to either estimate energy balance components or
278 to integrate (or calibrate) particular input data. In order to interpolate remote sensing data
279 temporally, ground measurements are required. The SVAT models can predict energy
280 exchanges without remote sensing information (Baldocchi et al., 2001), although Olioso et al.
281 (2005), Jupp (1998), and Voogt and Oke (2003) highlighted several benefits of combining
282 remote sensing data and SVAT models for ET estimation.

283 SVAT models need detailed surface and meteorological data. The third-generation SVATs
284 considers photosynthesis, carbon assimilation and biochemical reactions in order to
285 determine carbon, water vapour and energy exchange (Niogi et al., 2009; Anderson et al.,
286 2000). These models have been applied at both the leaf scale and regional scale. In these
287 approaches, carbon assimilation is equivalent to the photosynthesis rate. Even though leaf
288 photosynthesis leads to a carbon flux, it is dependent on light intensity, carbon concentration
289 and water stress.

290 Unlike the residual approach, deterministic methods can be used on cloudy days when remote
291 sensing images are not available. Owen et al. (1998) assessed vegetation factors and surface
292 moisture availability in urban mixed vegetated surfaces using the SVAT model. They
293 claimed that a small change in land cover index (the influence of local land cover
294 surrounding urbanized pixels) through urbanization dramatically changes the
295 evapotranspiration rate. Mauser and Schaldich (1998) modelled the spatial variation of ET at

296 micro and macro scales by introducing PROMET (Process Oriented Model for
297 Evapotranspiration), which is in the family of SVAT models.

298 *2.5 Other categorisations*

299 Other researchers have proposed their own categories, the most common of which are now
300 discussed. Contreras et al. (2011) suggested two main groups of RS application in ET
301 prediction, namely physically-based algorithms and indirect residual techniques. A
302 physically-based algorithm usually relies on the Penman-Monteith equation (a principle
303 method to estimate reference evapotranspiration). Indirect residual techniques quantify
304 surface energy balance parameters together with surface temperature/vegetation indices and
305 the numerical process of SVAT. Recently, Allen et al. (2011a) proposed two main categories,
306 namely remote sensing energy balance techniques and satellite-based ET using vegetation
307 indices. The former evaluates an energy balance through sensible heat flux using different
308 models (e.g. SEBAL, METRIC - Mapping Evapotranspiration at High Resolution and with
309 Internalized Calibration), mostly coupled with field measurements. Allen et al.'s second
310 category simply employs a vegetation index to estimate crop coefficients based on the close
311 relationship between vegetation (NDVI, VI or LAI) and transpiration. They claimed that the
312 basal coefficient has the most consistent relationship with NDVI.

313 **2. Advantages and disadvantages of remote sensing approaches**

314 Combining satellite image and ground-based techniques has enhanced the accuracy of
315 climatology data and particularly ET measurements (Wilson et al., 2003). Despite the
316 advantages of using remote sensing techniques to measure ET, several disadvantages have
317 also been reported. These include the time period between satellite captures, the high costs
318 associated with obtaining high resolution images particularly airborne images, the uncertainty
319 in estimating aerodynamic components and some errors in measuring narrow vegetation areas

320 such as riparian zones (Allen et al., 2011b;Boegh et al., 2009;Chen et al., 2005;Courault et
321 al., 2005b;Jiang et al., 2009;McCabe and Wood, 2006;Min and Lin, 2006;Mutiga et al.,
322 2010;Rana and Katerji, 2000;Stisen et al., 2008;Wu et al., 2010). It should also be noted that
323 temporal differences between satellite/airborne images can result not only from spectral
324 changes but also from daily, monthly, and yearly changes in sun position which directly
325 affect vegetation density (Weng et al., 2004). Bastiaanssen et al. (1998) suggested that
326 SEBAL does not work on cloudy days. Also, SEBAL has a specific regression model that
327 may not be suitable for all locations. Courault et al. (2005a) stated that climate data has an
328 important role in the SEBAL method and the accuracy of results is related to the density of
329 meteorological stations in the study area. Moreover, they provided the following table of
330 advantages and disadvantages of remote sensing approaches for ET estimation (Table 2).

331 Spatial variability models, such as SEBAL, METRIC and triangular models, tend to be
332 context-dependent. Long and Singh (2013) declared that hot and cold extremes may have a
333 similar impact on the inconsistency between the ratio of latent heat flux to available energy
334 and ground-based measurements. For instance, wet/dry pixels (edges) that are required to
335 trigger these models may not necessarily exist within a specific extent of an image. As the
336 extent and/or spatial resolution of a satellite image vary, the wet/dry limits of ET change
337 significantly and this results in different model outputs, i.e. the ET estimates from these
338 models are not deterministic. One of the concerns with the SEBAL model is the extent of the
339 study site in order for the operator to properly select the hot/wet pixels to satisfy the SEBAL
340 assumptions. In the hot extreme, LE is assumed to be zero and H is equal to the available
341 energy while for the cold extreme, H is assumed to be zero and LE is equal to the available
342 energy. Also, the meteorological and vegetation surface conditions should be generally
343 homogeneous so that the linear correlation between the near surface temperature and the
344 remotely sensed surface temperature holds true. In many cases, even a very large extent

345 would not necessitate the existence of both hot and wet extremes. For instance, one would
346 not be able to select a hot pixel from a large homogeneous forest. Secondly, there is not any
347 approach for the SEBAL/METRIC models to automate selection of extreme pixels from
348 images with varying extents, spatial resolutions and clouds (Long et al., 2011). Finally, even
349 when extremes can be properly selected from relatively large images, the SEBAL-type
350 algorithms appear to be limited in providing reasonable ET patterns due mostly to the use of
351 constant coefficients a and b in the SEBAL H algorithm. These constants do not
352 accommodate the effect of variations in fractional vegetation cover on ET extremes (Long
353 and Singh, 2012b; Long and Singh, 2013).

354 Due to the importance of water and carbon budget assessment in regional water management,
355 some researchers have recommended including biochemical and biophysical land surface
356 models to improve ET estimation. Significant correlation of system fluxes of ET (canopy
357 component assimilation and transpiration) with NDVI illustrates the importance of using
358 coupled modelling considering biochemical photosynthesis models and surface energy and
359 water balance frameworks at regional scales. However, while ET estimation approaches that
360 rely only on vegetation indices could potentially miss temporal variability resulting from
361 increased soil evaporation or vegetation stress (Anderson et al., 2008), the current study has
362 chosen to adopt a computationally efficient approach which appears to work well for the case
363 of mixed vegetation in urban parklands.

364 Allen et al. (2011a) asserted that in-situ measurements using the energy balance technique are
365 time consuming and need extensive skills, while remote sensing-based ET prediction using
366 vegetation indices involves rapid analyses for a large area and these can be performed by a
367 mid-level skilled technician. However, in this approach the effects of ET from rainfall events
368 between satellite overpasses might be missed but this does not diminish the importance of the
369 relationship between ET and vegetation indices. There are several studies showing a strong

370 correlation between ET and vegetation indices (Glenn et al.; Rossato et al., 2005; Nagler et
371 al., 2007; Palmer et al., 2009; Devitt et al., 2010; Johnson and Belitz, 2012; Nagler et al.,
372 2012). The authors agree with Allen's viewpoint in terms of the simplicity and quickness of
373 RS-based ET estimation using vegetation indices. Here the ET-VI relationships for
374 agricultural vegetation and mixed landscape vegetation are reviewed.

375 **3. Relationship between vegetation indices and ET**

376 Remote sensing applications have been expressively involved in estimation of canopy cover,
377 vegetation index, or leaf area index both in agricultural and non-agricultural (urban, forest...)
378 environments. Canopy cover as a direct driver of plant water demand and its relationship
379 with plant adjustment factor is a suitable indicator of plants evapotranspiration rate.

380 *3.1 Relationship between agricultural vegetation indices and ET*

381 Vegetation indices have been developed and successfully assessed evapotranspiration in the
382 last four decades particularly in the agricultural studies (Glenn et al., 2008). A new
383 generation of vegetation indices data particularly NDVI from Worldview 2, GeoEye, or
384 IKONOS provide high resolution coverage of the earth at less than a meter pixel resolution.
385 Duchemin et al. (2006) investigated the practicality of using remotely sensed NDVI as an
386 indirect method of estimating LAI and reference evapotranspiration, ET_{ref} . They proposed a
387 linear relationship between NDVI and basal crop coefficient for irrigated agricultural fields.
388 Tasumi and Allen (2007) studied the relationship between ET, crop behaviour, vegetation
389 indices (NDVI) and crop coefficients (derived from satellite images) for several crops during
390 their growing stages. They found NDVI as a helpful indicator to understand irrigation
391 consumption and assess irrigation management.

392 Trout and Johnson (2007) estimated the water demand of agricultural crops by calculating
393 crop coefficients and ET_{ref} from a weather station. Due to the high variability of crop

394 coefficients, an alternative method of measuring the crop coefficient based on light
395 interception by the canopy cover was introduced. This uncomplicated approach was able to
396 estimate the crop coefficient from its relationship with the basal crop coefficient. The crop
397 coefficients were estimated by remotely sensed NDVI. A multi-spectral camera was
398 employed to measure canopy cover while the basal crop coefficient was derived from
399 lysimeter measurements and meteorological parameters. In another study, Trout et al. (2008)
400 used a multi-spectral camera to measure canopy cover directly from horticultural crops. They
401 then compared the canopy cover derived from this method with that measured using remotely
402 sensed NDVI. They asserted that there was a high correlation and a linear relationship
403 between crop canopy and NDVI and recommended the application of remotely sensed NDVI
404 to predict vegetation water demand.

405 Later, O'Connell et al. (2009) determined the irrigation demand of citrus, grape, and almond
406 irrigation sites in Australia by ET measurement using the SEBAL model. The relationship
407 between ET and NDVI was also investigated. The results showed a strong relationship
408 between ET and NDVI for three crop species. Trout et al. (2010) compared the two remote
409 sensing techniques of energy balance (SEBAL) and an indirect method using vegetation
410 index in order to predict ET. They confirmed that vegetation cover can be estimated from
411 satellite-based NDVI for a wide variety of crops (Trout, 2011; Trout et al., 2010). Contreras et
412 al. (2011) estimated ET from irrigated and natural oases in central Argentina using a linear
413 relationship between ET and vegetation index at seasonal and annual temporal scales. Season
414 1 was the growing season from October to April and Season 2 was the dormant season from
415 May to September. They compared remotely sensed ET estimations with ground-based ET
416 measurements at the plot and basin spatial scales (Fig. 1). They concluded that a satellite
417 image approach is an uncomplicated and robust method with two to eighteen percent
418 uncertainty.

419 *3.2 Relationship between non-agricultural mixed vegetation indices and ET*

420 Remotely-sensed spatial, spectral, and temporal data can prominently enhance the ecological
421 knowledge of mixed landscape vegetation environment. Integration of ground-based field
422 measurement and RS-based data to calculate spectral vegetation indices (e.g. NDVI) simplify
423 and enhance the accuracy of ET estimation of mixed planting (Buyantuyev et al., 2007).

424 Keith et al. (2002) determined the spatial and temporal variability of vegetation greenness
425 through NDVI in Galveston Bay (Texas) for the six continues years. The NDVI time series
426 were compared with ground measurement climate data particularly evapotranspiration. They
427 asserted that remotely-sensed NDVI coupled with weather data is a useful tool to monitor
428 water usage in sub-watershed scales. Nagler et al. (2004) compared LAI measured using a
429 plant canopy analyzer, NDVI measured by a hand-held radiometer and the NDVI calculated
430 using low-level aerial photographs of natural riparian species along the Colorado River. They
431 compared the results from LAI and NDVI and reported 10% coefficients of variation (CV)
432 for NDVI in contrast to 40% CVs for LAI measurement. They asserted that for mixed
433 vegetation with different plant cover, NDVI provides more reliable information of
434 physiological processes with lower CVs. Rossato et al. (2005) analysed long-term satellite
435 data to study the spatial and temporal variability of ET in Brazil. They reported a near linear
436 relationship between ET and NDVI and recommended NDVI measurement as an indirect
437 method of ET monitoring for different types of trees and ground covers.

438 Three independent in-situ methods of evaluating soil moisture conditions; sap flow, open top
439 chamber, and eddy covariance were applied in a varied and multistorey vegetation areas in
440 Australia to measure evapotranspiration (Cook et al., 1998; Hutley et al., 2000). Later on,
441 Palmer et al. (2009) developed the MODIS LAI-ET model to estimate ET over the same
442 place. Results were validated and compared with previous ground-based research. They

443 found results driven from MODIS LAI-ET model closely approximate to ground
444 measurements. This model can be scaled-up to the catchment.

445 Boegh et al. (2009) used the water balance equation and investigated its relationship to ET for
446 natural vegetation through the vegetation parameters of LAI and crop coefficient. They found
447 a close agreement between canopy growth and evapotranspiration rate predominantly in
448 forests. Devitt et al. (2010) estimated the ET of mixed shrubs and grasslands in three valleys
449 in Nevada (USA) over a three year period. ET prediction was based on an energy balance
450 using the eddy covariance method and this was scaled up for entire catchments using remote
451 sensing data. They also investigated the correlation between ET and NDVI. The vegetation
452 density was categorized into 0 to 0.1 for low density, 0.1 to 0.25 for moderate density, and
453 more than 0.25 for high density. Their results confirmed the strong relationship ($r^2 = 97\%$,
454 $P < 0.001$) between ET and NDVI (Fig. 2).

455 Recently, Johnson and Belitz (2012) introduced a new approach of using NDVI to quantify
456 urban irrigation. Landsat Thematic Mapper satellite imagery, air photos, land-use maps, and
457 climatic data were employed to predict the location and monthly irrigation rate in urban
458 environments. They found the computed irrigation rate well correlated to actual
459 evapotranspiration data.

460 **4. Conclusion**

461 An accurate estimation of ET is highly important to have sustainable irrigation management
462 and healthy vegetation both in agricultural and non-agricultural environs. **Increasing**
463 **urbanisation, growing population and water scarcity are all major issues facing Australian**
464 **society. Urban parklands will have an important role in creating a healthy society and this**
465 **provides a key motivation for this study to review the water demand of urban green spaces**
466 **(Nouri et al. 2012). The study has found that remote sensing provides an efficient approach**
467 **for prediction of parkland water demand.**

468 Remote sensing had a great contribution in obtaining a more accurate ET estimation in both
469 pixel-scales to global-scale studies. Increasing the accessibility and resolution of remote
470 sensing data enables broad spatial coverage, routine updating, and the ability to provide self-
471 consistent measurements of critical physical properties that would be difficult or expensive to
472 obtain in situ (Miller and Small, 2003). It also provides the opportunity of automated data
473 collection covering spatially extensive and geographically discrete information in mixed
474 vegetation conditions.

475 This review has compared various remote sensing methods for estimating ET. Based on the
476 most comprehensive categorization of RS application in ET estimation, four main categories
477 of empirical direct, residual, inference, and deterministic were described. Semi-empirical
478 relationship between net radiation and cumulative surface and air temperature differences
479 characterise is the basis of the empirical direct approach. In the residual method, the
480 empirical and physical relationships are combined to estimate the energy balance
481 components directly through remote sensing and ET is estimated as the residual of the energy
482 balance equation. Inference approach is based on RS application to measure a reduction
483 adjustment factor to modify the reference evapotranspiration and achieve the actual ET of the
484 specific plants. Deterministic method investigates the complex relationship of soil,
485 vegetation, atmosphere transfer through complex models.

486 The spatial and temporal variation of heterogeneous mixed landscape vegetation areas
487 persuades finding a suitable approach with a higher capability of frequent update and spatial
488 resolution. Between all described methods, supporting Allen's view, the authors recommend
489 inference methods for the mixed landscape vegetation environs. Since, this approach is not
490 only simple and rapid compared to others, but also has the capability of observing the
491 heterogeneity of vegetation through Hyperspectral imageries. Some examples ET-VI
492 relationships in agricultural field and mixed landscape vegetation areas were described to

493 support the suitability and practicability of this approach. However, still several challenges are
494 presented in ET estimation using RS images such as long turn-around time of image
495 acquisition and the cost for the high resolution satellites.

496 The selection of the most appropriate approach is varied be based on the accuracy, budget,
497 time limitations, desired spatial and temporal resolutions, availability of ground data, and
498 particularly meteorological data.

499

500

501

502

503

504

505

506

507

508

509

510

511

512

513 **References**

- 514 Allen, R. G., Pereira, L. S., Howell, T. A., and Jensen, M. E.: Evapotranspiration information reporting: I.
515 Factors governing measurement accuracy, *Agricultural Water Management*, 98, 899-920, DOI:
516 10.1016/j.agwat.2010.12.015, 2011a.
- 517 Allen, R. G., Pereira, L. S., Howell, T. A., and Jensen, M. E.: Evapotranspiration information reporting: II.
518 Recommended documentation, *Agricultural Water Management*, 98, 921-929,
519 10.1016/j.agwat.2010.12.016, 2011b.
- 520 Allen, R. G., Pereira, L. S., Raes, D., and Smith, M.: Crop evapotranspiration - Guidelines for computing crop
521 water requirements - FAO Irrigation and drainage paper 56, FAO - Food and Agriculture Organization of
522 the United Nations, Rome, 1998.
- 523 Allen, R. G., Tasumi, M., Morse, A., and Trezza, R.: A Landsat-based energy balance and evapotranspiration
524 model in Western US water rights regulation and planning, *Irrigation and Drainage Systems*, 19, 251-268,
525 10.1007/s10795-005-5187-z, 2005.
- 526 Allen, R. G.: Using the FAO-56 dual crop coefficient method over an irrigated region as part of an
527 evapotranspiration intercomparison study, *Journal of Hydrology*, 229, 27-41, 10.1016/S0022-
528 1694(99)00194-8, 2000.
- 529 Anderson, F.: Hydrological modelling in a semi-arid area using remote sensing data, PhD thesis in University of
530 Copenhagen, 2008.
- 531 Anderson, M. C., Allen, R. G., Morse, A., and Kustas, W. P.: Use of Landsat thermal imagery in monitoring
532 evapotranspiration and managing water resources, *Remote Sensing of Environment*, 122, 50-65, 2012.
- 533 Anderson, M. C., Norman, J. M., Mecikalski, J. R., Otkin, J. A., and Kustas, W. P.: A climatological study of
534 evapotranspiration and moisture stress across the continental United States based on 2 thermal remote
535 sensing: 1. Model formulation, *Journal of Geophysical Research-Atmospheres*, 112, 2007.
- 536 Anderson, M. C., Norman, J. M., Kustas, W. P., Houborg, R., Starks, P. J., and Agam, N.: A thermal-based
537 remote sensing technique for routine mapping of land-surface carbon, water and energy fluxes from field
538 to regional scales, *Remote Sensing of Environment*, 112, 4227- 4241, 2008.
- 539 Anderson, N., Norman, J., Meyers, T., Diak, G.: An analytical model for estimating canopy transpiration and
540 carbon assimilation fluxes based on canopy light use efficiency. *Agric. For. Meteorol.*, 101, 265–289, 2000.
- 541 Baldocchi, D., Dennis, D., and Kell, B.: Modeling CO₂ and water vapor exchange of a temperate broadleaved
542 forest across hourly to decadal time scales, *Ecological Modelling*, 142, 155-184, 10.1016/S0304-
543 3800(01)00287-3, 2001.
- 544 Bastiaanssen, W. G. M., Ahmad, M. U. D., and Chemin, Y.: Satellite surveillance of evaporative depletion
545 across the Indus Basin, *Water Resour Res*, 38(12), 1273, 2002.
- 546 Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A., and Holtslag, A. A. M.: A remote sensing surface energy
547 balance algorithm for land (SEBAL). 1. Formulation, *Journal of Hydrology*, 212-213, 198-212,
548 10.1016/S0022-1694(98)00253-4, 1998.
- 549 Boegh, E., Poulsen, R. N., Butts, M., Abrahamsen, P., Dellwik, E., Hansen, S., Hasager, C. B., Ibrom, A.,
550 Loerup, J. K., Pilegaard, K., and Soegaard, H.: Remote sensing based evapotranspiration and runoff
551 modeling of agricultural, forest and urban flux sites in Denmark: From field to macro-scale, *Journal of*
552 *Hydrology*, 377, 300-316, DOI: 10.1016/j.jhydrol.2009.08.029, 2009.
- 553 Boegh, E., Soegaard, H., Hanan, N., Kabat, P., and Lesch, L.: A Remote Sensing Study of the NDVI-Ts
554 Relationship and the Transpiration from Sparse Vegetation in the Sahel Based on High-Resolution
555 Satellite Data, *Remote Sensing of Environment*, 69, 224-240, [http://dx.doi.org/10.1016/S0034-
556 4257\(99\)00025-5](http://dx.doi.org/10.1016/S0034-4257(99)00025-5), 1999.
- 557 Burt, C. M., Mutziger, A. J., Allen, R. G., and Howell, T. A.: Evaporation Research: Review and Interpretation,
558 *Journal of Irrigation and Drainage Engineering*, 131, 37-58, 2005.
- 559 Buyantuyev, A., Wu, J., and Gries, C.: Estimating vegetation cover in an urban environment based on Landsat
560 ETM+ imagery: A case study in Phoenix, USA, *International Journal of Remote Sensing archive*, 28, 269-
561 291, 2007.
- 562 Calcagno, G., Mendicino, G., Monacelli, G., Senatore, A., and Versace, P.: Distributed estimation of actual
563 evapotranspiration through remote sensing techniques, in: *Methods and Tools for Drought Analysis and*
564 *Management*, edited by: Rossi, G., Vega, T., and Bonaccorso, B., 62, Springer, Series: Water Science and
565 Technology Library, 124-147, 2007.
- 566 Carlson, T. N., Gillies, R. R., and Schmugge, T. J.: An interpretation of methodologies for indirect measurement
567 of soil water content, *Agricultural and Forest Meteorology*, 77, 191-205, 1995.
- 568 Carlson, T. N., Gillies, R. R. and Perry, E. M.: A method to make use of thermal infrared temperature and
569 NDVI measurements to infer surface soil water content and fractional vegetation cover, *Remote Sensing*
570 *Reviews*, 9, 161-173, 1994.

571 Chen, J. M., Chen, X., Ju, W., and Geng, X.: Distributed hydrological model for mapping evapotranspiration
572 using remote sensing inputs, *Journal of Hydrology*, 305, 15-39, DOI: 10.1016/j.jhydrol.2004.08.029, 2005.

573 Consoli, S., D'Urso, G., and Toscano, A.: Remote sensing to estimate ET-fluxes and the performance of an
574 irrigation district in southern Italy, *Agricultural Water Management*, 81, 295-314,
575 10.1016/j.agwat.2005.04.008, 2006.

576 Contreras, S., Jobbágy, E. G., Villagra, P. E., Nosetto, M. D., and Puigdefábregas, J.: Remote sensing estimates
577 of supplementary water consumption by arid ecosystems of central Argentina, *Journal of Hydrology*, 397,
578 10-22, 10.1016/j.jhydrol.2010.11.014, 2011.

579 Cook, P. G., Hatton, T. J., Pidsley, D., Herczeg, A. L., Held, A., O'Grady, A., and Eamus, D.: Water balance of
580 a tropical woodland ecosystem, Northern Australia: a combination of micro-meteorological, soil physical
581 and groundwater chemical approaches, *Journal of Hydrology*, 210, 161-177, 1998.

582 Courault, D., Seguin, B., and Olioso, A.: Review on estimation of evapotranspiration from remote sensing data:
583 From empirical to numerical modeling approaches, 223-249, 19, 233-249, 2005.

584 Devitt, D. A., Fenstermaker, L. F., Young, M. H., Conrad, B., Baghzouz, M., and Bird, B. M.:
585 Evapotranspiration of mixed shrub communities in phreatophytic zones of the Great Basin region of
586 Nevada (USA), *Ecohydrology*, 4, 807-822, 10.1002/eco.169, 2010.

587 Devitt, D. A., Fenstermaker, L. F., Young, M. H., Conrad, B., Baghzouz, M., Bird, B. M.: Evapotranspiration of
588 mixed shrub communities in phreatophytic zones of the Great Basin region of Nevada (USA).
589 *Ecohydrology* 4, 6, 807-822, 2010.

590 Drexler, J. Z., Snyder, R. L., Spano, D., and Paw U, K. T.: A review of models and micrometeorological
591 methods used to estimate wetland evapotranspiration, *Hydrological Processes*, 18, 2071-2101,
592 10.1002/hyp.1462, 2004.

593 Duchemin, B., Hadria, R., Erraki, S., Boulet, G., Maisongrande, P., Chehbouni, A., Escadafal, R., Ezzahar, J.,
594 Hoedjes, J. C. B., Kharrou, M. H., Khabba, S., Mougenot, B., Olioso, A., Rodriguez, J. C., and
595 Simonneaux, V.: Monitoring wheat phenology and irrigation in Central Morocco: On the use of
596 relationships between evapotranspiration, crops coefficients, leaf area index and remotely-sensed
597 vegetation indices, *Agricultural Water Management*, 79, 1-27, DOI: 10.1016/j.agwat.2005.02.013, 2006.

598 Fisher, J. B., Tu, K. P., and Baldocchi, D. D.: Global estimates of the land-atmosphere water flux based on
599 monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites, *Remote Sens Environ*, 112(3),
600 901-919, 2008.

601 Flagg, D.D. and Taylor, P. A.: Sensitivity of mesoscale model urban boundary layer meteorology to the scale of
602 urban representation. *Atmos. Chem. Phys.*, 11, 2951-2972, 2011.

603 Galleguillos, M., Jacob, F., Prévot, L., French, A., and Lagacherie, P.: Comparison of two temperature
604 differencing methods to estimate daily evapotranspiration over a Mediterranean vineyard watershed from
605 ASTER data, *Remote Sensing of Environment*, 115, 1326-1340, 10.1016/j.rse.2011.01.013, 2011.

606 Gillies, R. R., Kustas, W. P., and Humes, K. S.: A verification of the 'triangle' method for obtaining surface soil
607 water content and energy fluxes from remote measurements of the Normalized Difference Vegetation
608 Index (NDVI) and surface, *International Journal of Remote Sensing*, 18, 3145-3166,
609 10.1080/014311697217026, 1997.

610 Glenn, E. P., Huete, A. R., Nagler, P. L., Hirschboeck, K. K., and Brown, P.: Integrating Remote Sensing and
611 Ground Methods to Estimate Evapotranspiration, *Critical Reviews in Plant Sciences*, 26, 139 - 168, 2007.

612 Glenn, E., Huete, A., Nagler, P., and Nelson, S.: Relationship Between Remotely-sensed Vegetation Indices,
613 Canopy Attributes and Plant Physiological Processes: What Vegetation Indices Can and Cannot Tell Us
614 About the Landscape, *Sensors*, 8, 2136-2160, 2008.

615 Glenn, E., Huete, S., Nagler, P., and Nelson, S.: Relationship between remotely-sensed vegetation indices,
616 canopy attributes and plant physiological processes: what vegetation indices can and cannot tell us about
617 the landscape. *Sensors* 8, 4, 2136-2160, 2008.

618 Houborg, R., Anderson, M. C., Daughtry, C. S. T., Kustas, W. P., and Rodell, M.: Using leaf chlorophyll to
619 parameterize light-use-efficiency within a thermal-based carbon, water and energy exchange model,
620 *Remote Sensing of Environment*, 115, 1694-1705, 2011.

621 Hutley, L. B., O'Grady, A. P., and Eamus, D.: Evapotranspiration from Eucalypt open-forest savanna of
622 Northern Australia, *Functional Ecology*, 14, 183-194, 10.1046/j.1365-2435.2000.00416.x, 2000.

623 Irmak, S., Haman, D.Z.: Evapotranspiration: Potential or reference. ABE 343, one of a series of the Agricultural
624 and Biological Engineering Department, Florida Cooperative Extension Service, Institute of Food and
625 Agricultural Sciences, University of Florida. Reviewed October 2011.

626 Jia, L., Su, Z., van den Hurk, B., Menenti, M., Moene, A., De Bruin, H. A. R., Yrisarry, J. J. B., Ibanez, M., and
627 Cuesta, A.: Estimation of sensible heat flux using the Surface Energy Balance System (SEBS) and ATSR

628 measurements, *Physics and Chemistry of the Earth, Parts A/B/C*, 28, 75-88, 10.1016/s1474-
629 7065(03)00009-3, 2003.

630 Jiang, L., and Islam, S.: Estimation of surface evaporation map over southern Great Plains using remote sensing
631 data, *Water Resour Res*, 37(2), 329-340, 2001.

632 Jiang, L., Islam, S., Guo, W., Singh Jutla, A., Senarath, S. U. S., Ramsay, B. H., and Eltahir, E.: A satellite-
633 based Daily Actual Evapotranspiration estimation algorithm over South Florida, *Global and Planetary*
634 *Change*, 67, 62-77, DOI: 10.1016/j.gloplacha.2008.12.008, 2009.

635 Johnson, T. D., and Belitz, K.: A remote sensing approach for estimating the location and rate of urban
636 irrigation in semi-arid climates, *Journal of Hydrology*, 414-415, 86-98, 10.1016/j.jhydrol.2011.10.016,
637 2012.

638 Jupp, D. L. B.: Directional radiance and emissivity measurement models for remote sensing of the surface
639 energy balance, *Environmental Modelling & Software*, 13, 341-351, 10.1016/s1364-8152(98)00039-
640 5, 1998.

641 Kalma, J., McVicar, T., and McCabe, M.: Estimating Land Surface Evaporation: A Review of Methods Using
642 Remotely Sensed Surface Temperature Data, *Surveys in Geophysics*, 29, 421-469, 10.1007/s10712-008-
643 9037-z, 2008.

644 Keith, D. J., Walker, H. A., and Paul, J. F.: Terrestrial vegetation greenness of the Lower Galveston Bay
645 watershed from satellite remote sensing and its relation to water use and the salinity regime of the
646 Galveston Bay Estuary (USA), *International Journal of Remote Sensing*, 23, 905-916,
647 10.1080/01431160110040486, 2002.

648 Kim, S. H., and Lieth, J.H.: A coupled model of photosynthesis, stomata conductance, and transpiration for a
649 rose leaf (*Rosa hybrid L.*). *Annals of Botany*, 91, 771-781, 2003.

650 Kustas, W. P., and Norman, J. M.: Use of remote sensing for evapotranspiration monitoring over land surfaces,
651 *Hydrological Sciences Journal*, 41, 495-516, 10.1080/02626669609491522, 1996.

652 Li, Z.-L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., and Zhang, X.: A Review of current
653 methodologies for regional evapotranspiration estimation from remotely sensed data, *Sensors*, 9, 3801-
654 3853, 2009.

655 Long, D., and Singh, V. P.: A Two-source Trapezoid Model for Evapotranspiration (TTME) from satellite
656 imagery, *Remote Sens Environ*, 121, 370-388, 2012a.

657 Long, D., and Singh, V. P.: A modified surface energy balance algorithm for land (M-SEBAL) based on a
658 trapezoidal framework, *Water Resour Res*, 4, 2012b.

659 Long, D., and Singh, V. P.: Assessing the impact of end-member selection on the accuracy of satellite-based
660 spatial variability models for actual evapotranspiration estimation, *Water Resour Res*, 49, 1-18, 2013.

661 Long, D., Singh, V. P., and Li, Z. L.: How sensitive is SEBAL to changes in input variables, domain size and
662 satellite sensor?, *Journal of Geophysical Research-Atmospheres*, 116, 2011.

663 Lucke, T., Johnson, T., Beecham, S., Cameron, D., and Moore, G.: Using permeable pavements to promote
664 street tree health, to minimize pavement damage and to reduce stormwater flows, 12th International
665 Conference on Urban Drainage, Porto Alegre, Brazil, 2011.

666 Mauser, W., and Schädlich, S.: Modelling the spatial distribution of evapotranspiration on different scales using
667 remote sensing data, *Journal of Hydrology*, 212-213, 250-267, 10.1016/s0022-1694(98)00228-5, 1998.

668 McCabe, M. F., and Wood, E. F.: Scale influences on the remote estimation of evapotranspiration using multiple
669 satellite sensors, *Remote Sensing of Environment*, 105, 271-285, DOI: 10.1016/j.rse.2006.07.006, 2006.

670 Miller, R. B., and Small, C.: Cities from space: potential applications of remote sensing in urban environmental
671 research and policy, *Environmental Science & Policy*, 6, 129-137, 10.1016/s1462-9011(03)00002-9,
672 2003.

673 Min, Q., and Lin, B.: Remote sensing of evapotranspiration and carbon uptake at Harvard Forest, *Remote*
674 *Sensing of Environment*, 100, 379-387, DOI: 10.1016/j.rse.2005.10.020, 2006.

675 Mutiga, J. K., Su, Z., and Woldai, T.: Using satellite remote sensing to assess evapotranspiration: Case study of
676 the upper Ewaso Ng'iro North Basin, Kenya, *International Journal of Applied Earth Observation and*
677 *Geoinformation*, 12, S100-S108, DOI: 10.1016/j.jag.2009.09.012, 2010.

678 Nagler, P. L., Brown, T., Hultine, K. R., Riper Iii, C. van, Bean, D. W., Dennison, P. E., Murray, R. S., and
679 Glenn, E. P.: Regional scale impacts of Tamarix leaf beetles (*Diorhabda carinulata*) on the water
680 availability of western U.S. rivers as determined by multi-scale remote sensing methods. *Remote Sensing*
681 *of Environment* 118, 227-238, 2012.

682 Nagler, P. L., Glenn, E. P., Lewis Thompson, T., and Huete, A.: Leaf area index and normalized difference
683 vegetation index as predictors of canopy characteristics and light interception by riparian species on the
684 Lower Colorado River, *Agricultural and Forest Meteorology*, 125, 1-17, 10.1016/j.agrformet.2004.03.008,
685 2004.

686 Nagler, P., Jetton, A., Fleming, J., Didan, K., Glenn, E., Erker, J., Morino, K., Milliken, J., and Gloss, S.:
687 Evapotranspiration in a cottonwood (*Populus fremontii*) restoration plantation estimated by sap flow and
688 remote sensing methods. *Agricultural and Forest Meteorology* 144, 1–2, 95–110, 2007.

689 Neale, C., Jayanthi, H., and Wright, J.: Irrigation water management using high resolution airborne remote
690 sensing, *Irrigation and Drainage Systems*, 19, 321–336, 10.1007/s10795-005-5195-z, 2005.

691 Niyogi, D., Alapaty, K., Raman, S., and Chen, F. : Development and evaluation of a coupled photosynthesis-
692 based gas exchange evapotranspiration model (GEM) for mesoscale weather forecasting applications.
693 *Journal of Applied Meteorology and Climatology*, 48, 349–357, 2007.

694 Norman, J. M., Kustas, W. P., and Humes, K. S.: A two-source approach for estimating soil and vegetation
695 energy fluxes in observations of directional radiometric surface-temperature, *Agr Forest Meteorol*, 77,
696 263–293, 1995.

697 Nouri, H., Beecham, S., and Hassanli, A. M., Kazemi, F.: Water requirements of urban landscape plants: a
698 comparison of three factor-based approaches, *Ecological Engineering*, 2013.

699 Nouri, H., Beecham, S., Kazemi, F., and Hassanli, A. M.: A review of ET measurement techniques for
700 estimating the water requirements of urban landscape vegetation, *Urban Water Journal*, 1–13,
701 10.1080/1573062x.2012.726360, 2012.

702 O’Connell, M., Whitfield, D., Abuzar, M., K. Sheffield, McClymont, L., and McAllister, A.: Satellite remote
703 sensing of crop water use in perennial horticultural crops, VI International Symposium on Irrigation of
704 Horticultural Crops, Viña del Mar (Chile), 2009.

705 Olioso, A., Inoue, Y., Ortega-Farias, S., Demarty, J., Wigneron, J. P., Braud, I., Jacob, F., Lecharpentier, P.,
706 Ottlé, C., Calvet, J. C., and Brisson, N.: Future directions for advanced evapotranspiration modeling:
707 Assimilation of remote sensing data into crop simulation models and SVAT models, *Irrigation and*
708 *Drainage Systems*, 19, 377–412, 10.1007/s10795-005-8143-z, 2005.

709 Owen, T. W., Carlson, T. N., and Gillies, R. R.: An assessment of satellite remotely-sensed land cover
710 parameters in quantitatively describing the climatic effect of urbanization, *International Journal of Remote*
711 *Sensing*, 19, 1663–1681, 1998.

712 Palmer, A. R., Fuentes, S., Taylor, D., Macinnis-Ng, C., Zeppel, M., Yunusa, I., and Eamus, D.: Towards a
713 spatial understanding of water use of several land-cover classes : an examination of relationships amongst
714 pre-dawn leaf water potential, vegetation water use, aridity and MODIS LAI, *Ecohydrology*, 3: 1–10.
715 doi: 10.1002/eco.63, 2009.

716 Palmer, A. R., Fuentes, S., Taylor, D., Macinnis-Ng, C., Zeppel, M., Yunusa, I., and Eamus, D.: Towards a
717 spatial understanding of water use of several land-cover classes : an examination of relationships amongst
718 pre-dawn leaf water potential, vegetation water use, aridity and MODIS LAI, 2009.

719 Phinn, S., Stanford, M., Scarth, P., Murray, A. T., and Shyy, P. T.: Monitoring the composition of urban
720 environments based on the vegetation-impervious surface-soil (VIS) model by subpixel analysis
721 techniques, *International Journal of Remote Sensing*, 23, 4131–4153, 10.1080/01431160110114998, 2002.

722 Rana, G., and Katerji, N.: Measurement and estimation of actual evapotranspiration in the field under
723 Mediterranean climate: a review, *European Journal of Agronomy*, 13, 125–153, Doi: 10.1016/s1161-
724 0301(00)00070-8, 2000.

725 Ridd, M. K.: Exploring a V-I-S (vegetation-impervious surface-soil) model for urban ecosystem analysis
726 through remote sensing: comparative anatomy for cities, *Int. J. Remote Sens.*, 16, 2165–2185, 1995.

727 Roerink, G. J., Su, Z., and Menenti, M.: S-SEBI: A simple remote sensing algorithm to estimate the surface
728 energy balance, *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, 25, 147-
729 157, 2000.

730 Rossato, L., Alvala, R. C. S., Ferreira, N. J., and Tomasella, J.: Evapotranspiration estimation in the Brazil using
731 NDVI data, Brugge, Belgium, 2005, 59761G-59769, 2005.

732 Rwasoka, D. T., Gumindoga, W., and Gwenzi, J. V.: Estimation of actual evapotranspiration using the Surface
733 Energy Balance System (SEBS) algorithm over land surfaces, *Physics and Chemistry of the Earth, Parts*
734 *A/B/C*, In Press, Accepted Manuscript, 10.1016/j.pce.2011.07.035, 2011.

735 Senay, G. B., Budde, M. E., and Verdin, J. P.: Enhancing the Simplified Surface Energy Balance (SSEB)
736 approach for estimating landscape ET: Validation with the METRIC model, *Agricultural Water*
737 *Management*, 98, 606–618, 10.1016/j.agwat.2010.10.014, 2011.

738 Silberstein, R., Held, A., Hatton, T., Viney, N., and Sivapalan, M.: Energy balance of a natural jarrah
739 (*Eucalyptus marginata*) forest in Western Australia: measurements during the spring and summer,
740 *Agricultural and Forest Meteorology*, 109, 79–104, Doi: 10.1016/s0168-1923(01)00263-5, 2001.

741 Small, C., and Lu, J. W. T.: Estimation and vicarious validation of urban vegetation abundance by spectral
742 mixture analysis, *Remote Sensing of Environment*, 100, 441–456,
743 <http://dx.doi.org/10.1016/j.rse.2005.10.023>, 2006.

744 Small, C.: High spatial resolution spectral mixture analysis of urban reflectance, *Remote Sensing of*
745 *Environment*, 88, 170-186, 10.1016/j.rse.2003.04.008, 2003.

746 Sobrino, J. A., Gomez, M., Jimenez-Munoz, J. C., Oliso, A., and Chehbouni, G.: A simple algorithm to
747 estimate evapotranspiration from DAIS data: Application to the DAISEX campaigns, *Journal of*
748 *Hydrology*, 315, 117-125, 10.1016/j.jhydrol.2005.03.027, 2005.

749 Stisen, S., Sandholt, I., Nørgaard, A., Fensholt, R., and Jensen, K. H.: Combining the triangle method with
750 thermal inertia to estimate regional evapotranspiration -- Applied to MSG-SEVIRI data in the Senegal
751 River basin, *Remote Sensing of Environment*, 112, 1242-1255, DOI: 10.1016/j.rse.2007.08.013, 2008.

752 Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes, *Hydrology and*
753 *Earth System Sciences*, 6, 85-100, 10.5194/hess-6-85-2002, 2002a.

754 Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes, *Hydrology and*
755 *Earth System Sciences*, 6, 85-99, 2002b.

756 Sumantra, C.: A modified crop coefficient approach for estimating regional evapotranspiration, NASA/USDA
757 Workshop on Evapotranspiration, April 11-12, Maryland, USA, 2011.

758 Sun, Z., Wei, B., Su, W., Shen, W., Wang, C., You, D., and Liu, Z.: Evapotranspiration estimation based on the
759 SEBAL model in the Nansi Lake Wetland of China, *Mathematical and Computer Modelling*, 54, 1086-
760 1092, 10.1016/j.mcm.2010.11.039, 2011.

761 Tanaka, H., Hiyama, T., Kobayashi, N., Yabuki, H., Ishii, Y., Desyatkin, R. V., Maximov, T. C., and Ohta, T.:
762 Energy balance and its closure over a young larch forest in eastern Siberia, *Agricultural and Forest*
763 *Meteorology*, 148, 1954-1967, DOI: 10.1016/j.agrformet.2008.05.006, 2008.

764 Tang, R., Li, Z.-L., Jia, Y., Li, C., Sun, X., Kustas, W. P., and Anderson, M. C.: An intercomparison of three
765 remote sensing-based energy balance models using Large Aperture Scintillometer measurements over a
766 wheat-corn production region, *Remote Sensing of Environment*, In Press, Corrected Proof,
767 10.1016/j.rse.2011.07.004, 2011.

768 Tasumi, M., and Allen, R. G.: Satellite-based ET mapping to assess variation in ET with timing of crop
769 development, *Agricultural Water Management*, 88, 54-62, 10.1016/j.agwat.2006.08.010, 2007.

770 Tasumi, M., Trezza, R., Allen, R., and Wright, J.: Operational aspects of satellite-based energy balance models
771 for irrigated crops in the semi-arid U.S, *Irrigation and Drainage Systems*, 19, 355-376, 10.1007/s10795-
772 005-8138-9, 2005.

773 Teixeira, A. H., Bastiaanssen, W. G. M., Ahmad, M. D., and Bos, M. G.: Reviewing SEBAL input parameters
774 for assessing evapotranspiration and water productivity for the Low-Middle São Francisco River basin,
775 Brazil: Part A: Calibration and validation, *Agricultural and Forest Meteorology*, 149, 462-476,
776 10.1016/j.agrformet.2008.09.016, 2009.

777 Timmermans, W. J., Kustas, W. P., Anderson, M. C., and French, A. N.: An intercomparison of the Surface
778 Energy Balance Algorithm for Land (SEBAL) and the Two-Source Energy Balance (TSEB) modeling
779 schemes, *Remote Sensing of Environment*, 108, 369-384, 10.1016/j.rse.2006.11.028, 2007.

780 Trout, T. J., Johnson, L. F., and Gartung, J.: Remote Sensing of Canopy Cover in Horticultural Crops,
781 *HortScience*, 43, 333-337, 2008.

782 Trout, T., and Johnson, L.: Estimating Crop Water use From Remotely Sensed NDVI, *Crop Models and*
783 *Reference ET USCID Fourth International Conference on Irrigation and Drainage*, Sacramento, California
784 October 2007.

785 Trout, T., Johnson, L., Wang, D., and Clark, B.: Comparison of Two Remote Sensing Approaches for ET
786 Estimation in the San Joaquin Valley, 5th National Decennial Irrigation Conference Proceedings, Phoenix
787 Convention Center, Phoenix, Arizona USA, 2010.

788 Trout, T.: Remote Sensing Requirements for Scheduling Irrigations, NASA/USDA Workshop on
789 Evapotranspiration, Maryland, USA, 2011,

790 Vinukollu, R. K., Wood, E. F., Ferguson, C. R., and Fisher, J. B.: Global estimates of evapotranspiration for
791 climate studies using multi-sensor remote sensing data: Evaluation of three process-based approaches,
792 *Remote Sensing of Environment*, 115, 801-823, 10.1016/j.rse.2010.11.006, 2011.

793 Voogt, J. A., and Oke, T. R.: Thermal remote sensing of urban climates, *Remote Sensing of Environment*, 86,
794 370-384, 10.1016/s0034-4257(03)00079-8, 2003.

795 Wang, K., and Dickinson, R. E.: A review of global terrestrial evapotranspiration: Observation, modeling,
796 climatology, and climatic variability, *Reviews of Geophysics*, 50, n/a-n/a, 10.1029/2011rg000373, 2012.

797 Weber, D. and Anderson, D.: Contact with nature: recreation experience preferences in Australian parks. *Annals*
798 *of Leisure Research* 13, 46-73, 2010.

799 Weng, Q., Lu, D., and Schubring, J.: Estimation of land surface temperature-vegetation abundance relationship
800 for urban heat island studies, *Remote Sensing of Environment*, 89, 467-483, 10.1016/j.rse.2003.11.005,
801 2004.

802 Wilson, J. S., Clay, M., Martin, E., Stuckey, D., and Vedder-Risch, K.: Evaluating environmental influences of
803 zoning in urban ecosystems with remote sensing, *Remote Sensing of Environment*, 86, 303-321,
804 10.1016/s0034-4257(03)00084-1, 2003.

805 Wu, C., Cheng, C., Lo, H., and Chen, Y.: Study on estimating the evapotranspiration cover coefficient for
806 stream flow simulation through remote sensing techniques, *International Journal of Applied Earth
807 Observation and Geoinformation*, 12, 225-232, DOI: 10.1016/j.jag.2010.03.001, 2010.

808 Yang, J., and Wang, Y.: Estimating evapotranspiration fraction by modeling two-dimensional space of
809 NDVI/albedo and day-night land surface temperature difference: A comparative study, *Advances in Water
810 Resources*, 34, 512-518, 10.1016/j.advwatres.2011.01.006, 2011.

811 Yao, W., Han, M., and Xu, S.: Estimating the regional evapotranspiration in Zhalong wetland with the Two-
812 Source Energy Balance (TSEB) model and Landsat7/ETM+ images, *Ecological Informatics*, 5, 348-358,
813 10.1016/j.ecoinf.2010.06.002, 2010.

814 Yuan, F., and Bauer, M. E.: Comparison of impervious surface area and normalized difference vegetation index
815 as indicators of surface urban heat island effects in Landsat imagery, *Remote Sensing of Environment*,
816 106, 375-386, doi: 10.1016/j.rse.2006.09.003, 2007.

817 Yunusa, I. A. M., Walker, R. R., and Lu, P.: Evapotranspiration components from energy balance, sapflow and
818 microlysimetry techniques for an irrigated vineyard in inland Australia, *Agricultural and Forest
819 Meteorology*, 127, 93-107, DOI: 10.1016/j.agrformet.2004.07.001, 2004.

820 Zhang, K., Kimball, J. S., Nemani, R. R., and Running, S. W.: A continuous satellite-derived global record of
821 land surface evapotranspiration from 1983 to 2006, *Water Resour Res*, 46. DOI 10.1029/2009WR008800,
822 2010.

823

824

825

826

827

828

829

830

831

832

833

834

835

836 **List of tables:**

837 Table 1- Table of abbreviations

838 Table 2. Advantages and disadvantages of various remote sensing approaches for estimating ET

839 (after Courault et al., 2005b)

840

841

842

843

844

845

846

847

848

849

850

851

852

853

854

855

856 **List of figures:**

857 Fig.1 Relationship between ET and NDVI in three catchments in Nevada, USA (after Devitt et
858 al., 2010)

859 Fig. 2 Comparison of ET rates of ground-based (FAO-crop coefficient) and satellite-based
860 methods (after Contreras et al. 2011)

861

862

863

864

865

866

867

868

869

870

871

872

873

874

875

876 Table 1- Table of abbreviations

Remote Sensing	RS
Evapotranspiration	ET
Vegetation Index	VI
Stress Degree Day	SDD
Normalized Difference Vegetation Index	NDVI
Near Infrared	NIR
Surface Energy Balance Algorithm for Land	SEBAL
Surface Energy Balance Index	SEBI
Simplified Surface Energy Balance Index	S-SEBI
Surface Energy Balance System	SEBS
Two-Source Energy Balance	TSEB
Soil-Vegetation-Atmosphere Transfer	SVAT
Leaf Area Index	LAI
Process Oriented Model for Evapotranspiration	PROMET
Mapping Evapotranspiration at High Resolution and with Internalized Calibration	METRIC
Moderate-resolution Imaging Spectroradiometer	MODIS
Urban Heat Island	UHI
Digital Elevation Model	DEM
Food and Agriculture Organization	FAO
Coefficients of Variation	CV

877

878

879

880

881

882 Table 2. Advantages and disadvantages of various remote sensing approaches for estimating ET (after Courault
 883 et al., 2005b)

Method/model	Advantages	Disadvantages
Empirical Direct	Operational from local to regional scales	Spatial variation of coefficients
Interference model	Operational if combined with ground measurement methods or models	Requires calibration for each crop type K _c varies according to water stress
Residual (SEBAL, S-SEBI)	Low cost Needs no additional climatic data	Requires detection of wet and dry pixels
Deterministic (SVAT)	Permits estimation of intermediate variables such as LAI Possible links with climate and/or hydrological models	Requires more parameters Requires accurate remote sensing data

884

885

886

887

888

889

890

891

892

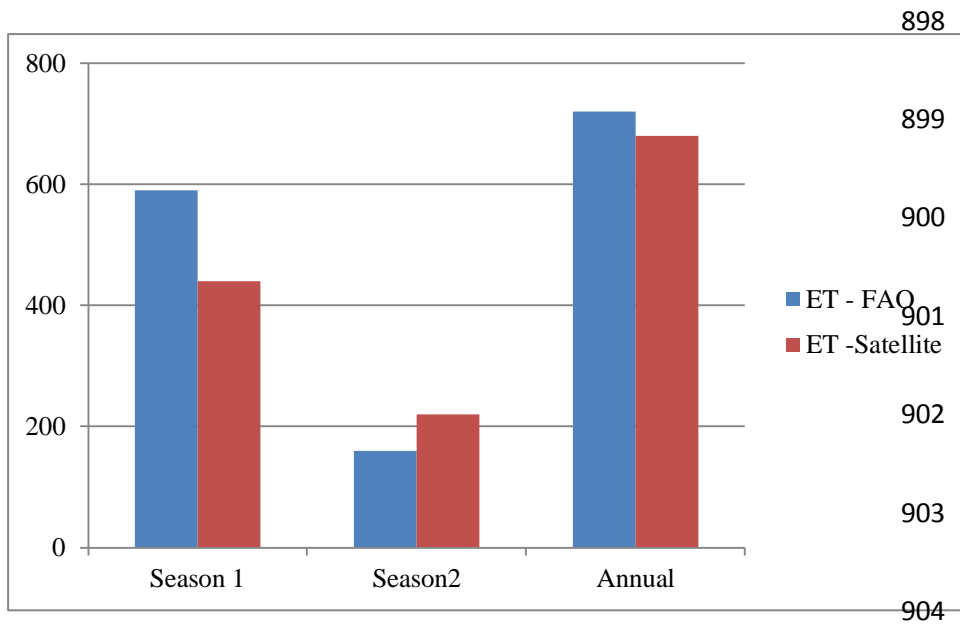
893

894

895

896

897



905 Fig. 1 Comparison of ET rates (mm y⁻¹) of ground-based (FAO-crop coefficient) and satellite-based methods
 906 (after Contreras et al. 2011)

907

908

909

910

911

912

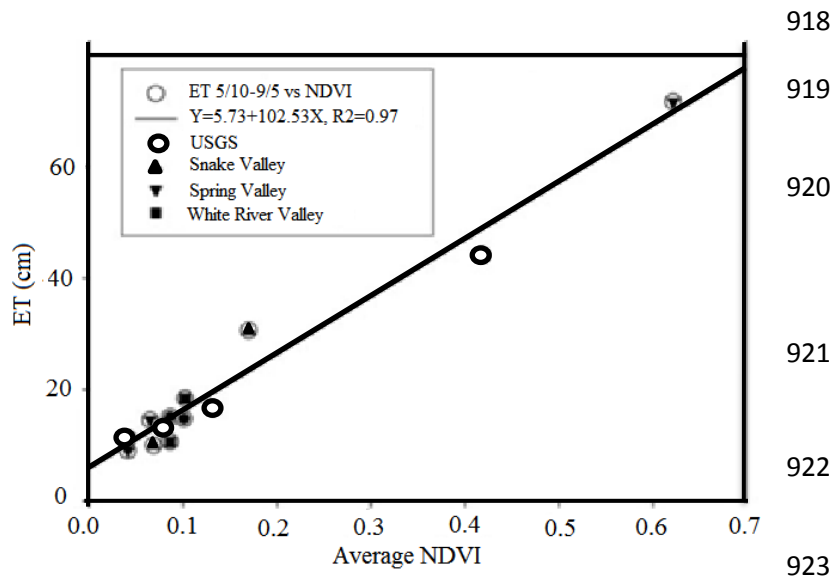
913

914

915

916

917



924 Fig.2 Relationship between yearly ET and NDVI in three catchments in Nevada, USA (after Devitt et al., 2010)

925

926

927

928

929